

MULTI-PARAMETER ALGORITHM TO ENHANCE REAL-TIME SPACE SHUTTLE MAIN PROPULSION SYSTEM FAULT DETECTION

Claudia Meyer and William A. Maul
NYMA Inc.
Brook Park, Ohio

Kenneth J. Dwyer
NASA JSC
Houston, Texas

June F. Zakrajsek
NASA LeRC
Cleveland, Ohio

ABSTRACT

Real-time algorithms which increase the ability to detect off-nominal Space Shuttle Main Engine (SSME) conditions during flight can improve Shuttle safety and reliability. Multi-parameter fault detection techniques have been targeted because they do not rely on a single parameter for fault information and thereby improve confidence in the detection. Furthermore, no assumptions regarding failure modes are required, permitting the detection of previously unencountered or unanticipated failures. The Clustering Algorithm, a multi-parameter fault detection approach that was originally trained and validated on SSME ground test firing data, was slightly modified and applied to SSME historical flight data; the application is documented in this report. Preliminary studies were conducted to assess the impact of different engines, different missions and different thrust profiles on the performance of the Clustering Algorithm. The algorithm successfully predicted sixteen performance parameters during mainstage operation of the engine when applied to nominal data sets and provided indications of off-nominal behavior when applied to data from an engine which had experienced an offset in one of the control parameters. The information from the Clustering Algorithm is intended to enhance the diagnostic information available to the NASA Johnson Space Center control room engineers during flight.

NOMENCLATURE

CCC	Central Control Complex
FPB	Fuel Preburner
FPOV	Fuel Preburner Oxidizer Valve
HPFP	High Pressure Fuel Pump
HPFT	High Pressure Fuel Turbine
HPOP	High Pressure Oxidizer Pump
HPOT	High Pressure Oxidizer Turbine
JSC	Johnson Space Center
LPFP	Low Pressure Fuel Pump
LPOP	Low Pressure Oxidizer Pump
LeRC	Lewis Research Center
LRU	Line Replaceable Unit
MCC	Main Combustion Chamber

MSFC	Marshall Space Flight Center
OPOV	Oxidizer Preburner Oxidizer Valve
PBP	Preburner Boost Pump
SRB	Solid Rocket Booster
SSME	Space Shuttle Main Engine
STS	Space Transportation System

INTRODUCTION

Engineers at the NASA Johnson Space Center (JSC) Central Control Complex (CCC) are responsible for monitoring the Space Transportation System (STS) Main Propulsion System following liftoff. The Main Propulsion System consists of three Space Shuttle Main Engines (SSMEs). In an effort to further facilitate and automate this activity, CCC engineers are considering the use of anomaly detection algorithms to enhance the current Space Shuttle Main Engine safety system during flight. Anomaly detection algorithms could improve Shuttle safety by distinguishing between nominal and off-nominal engine operation; some algorithms have the potential to provide additional information on failure type or location.

The current safety system on the SSME consists of redlines on parameters which have sensor hardware redundancy. When a qualified channel exceeds its redline limit for three consecutive cycles, engine shutdown is initiated.[1] These redlines were established in response to material and structural considerations. In looking at the SSME ground test firing database and, in particular, at the anomalies that have occurred, it was found that failure information is frequently present in the performance data prior to redline cutoff.[2]-[5] In fact, several parameters typically provide corroborating evidence that an engine hardware anomaly is occurring.

In order to improve fault detection capability for the SSME, the NASA Lewis Research Center (LeRC) funded the development of several multi-parameter fault detection approaches to cover both startup and mainstage operation of the engine.[4]-[7] Multi-parameter approaches combine the information from several non-redundant sensors into a single metric representative of the engine's condition. Multi-parameter approaches are desired since they do not rely on a single parameter for fault information and thereby improve confidence in the detection. Multi-parameter approaches are

inherently more robust to sensor failures than the current single parameter redlines. Moreover, multi-parameter approaches have the potential to provide fault isolation information. Emphasis in these studies was placed on the earliest possible detection of an off-nominal engine condition without issuing any erroneous fault indications. Specific failure modes were not targeted since the algorithm was designed to detect any off-nominal condition, including those not previously encountered.

One promising mainstage multi-parameter approach developed under the direction of NASA LeRC is the Clustering Algorithm. The Clustering Algorithm was extensively trained and validated on historical ground test firing data. For many of the major failures, the Clustering Algorithm indicated off-nominal engine conditions significantly earlier than redline cutoff. The algorithm also monitored several NASA Marshall Space Flight Center (MSFC) Technology Test Bed engine firings in real time.[7]

In order to assess the potential benefits that this algorithm could provide to CCC engineers, the Clustering Algorithm was applied to historical flight data; this report documents the application. In making the transition to flight data several modifications were introduced into the original algorithm in order to improve the fault coverage of the algorithm and to make the algorithm more consistent with the fault detection methodology used by experienced analysts. These modifications were made in response to issues raised by CCC engineers and recommendations made by the SSME Controller Enhancement Study team led by MSFC.

The clustering algorithm uses models which predict the nominal behavior of the engine. Data from five missions were used to train and evaluate Clustering Algorithm model sets. Of primary interest in this investigation was the prediction capability of the model sets. Four flight engine Clustering Algorithm model sets were generated; one used data from three engines, each from a different mission, while the other three used data from a single engine on a single mission. The capabilities of Clustering Algorithm model sets based on single and multiple engine data sets were compared. In addition, validation data sets were selected to assess the impact of different engines, different missions and different thrust profiles on the performance of the Clustering Algorithm under nominal conditions. Finally, one historical off-nominal data set was presented to the Clustering Algorithm.

THE JSC BOOSTER FLIGHT CONTROL TEAM

The Mission Operations Directorate at JSC is tasked with monitoring all Space Shuttle systems from liftoff through touchdown. Responsibilities include verifying that all hardware and software perform correctly and, if not, identifying impacts and producing procedures to handle the off-nominal conditions. These procedures must, at all times, protect the safety of each crew member, while completing the maximum number of flight objectives. The flight control team is composed of 18 different disciplines. The Booster flight control team is responsible for monitoring the SSMEs in real time.

The Booster flight control team consists of the Main Propulsion Operator, the Main Engine Operator, and the Booster Officer. The Main Propulsion Operator monitors

pressures, temperatures and flow rates in the External Tank, the Solid Rocket Boosters and the SSME propellant feed system. The Main Engine Operator is responsible for monitoring the overall health of each engine. The Booster Officer monitors the data seen by the two operators and interacts with other disciplines on the flight control team as required.

The major part of the Main Engine Operator's responsibility is to determine if the SSMEs are running at their preflight predicted values for mixture ratio, thrust level and specific impulse. Any discrepancies are reported to the Booster Officer; this notification includes quantitative values for the mixture ratio, thrust and specific impulse. These values are used by the Flight Dynamics Officer to determine if, based on the current vehicle position velocity and remaining usable propellant, the launch can be successfully completed.

The Main Engine Operator must also determine if an off-nominal case is occurring. Currently, nine pre-determined off-nominal cases are considered. Although these pre-determined cases have been adequate in diagnosing the two missions, STS-1 and STS-44, which have encountered off-nominal engine conditions to date, the technical community feels the need to develop a program which would assist the Main Engine Operator in detecting off-nominal cases which are currently not covered. Therefore, the Clustering Algorithm, a multivariable approach, is being investigated as a possible solution to identifying off-nominal engine performance without a priori fault information.

THE CLUSTERING ALGORITHM: BACKGROUND AND IMPLEMENTATION

The Clustering Algorithm is based on classical pattern recognition techniques. Nominal engine performance is characterized by establishing regions of nominal behavior in n-dimensional space. These regions are then used to classify new data when the algorithm is being used for fault detection. If a new n-dimensional data point falls within an empirically-derived threshold of the regions established by the nominal training data, this point is considered nominal. If the new n-dimensional data point does not fall within the empirically-derived threshold of the nominal clusters established by the training data, the new data point may indicate a faulty condition. Off-nominal classifications on multiple consecutive time slices can be used to declare an engine anomaly.

No assumptions regarding specific failure modes are required. Instead, the usefulness of the Clustering Algorithm depends on adequate characterization of nominal engine behavior. Nominal engine data are reduced into representative regions, each labeled by a cluster center, using a data clustering technique which makes a single pass through the data. These cluster centers are stored in the form of regression equations, where the inputs are the parameters given in Table 1. The Main Combustion Chamber (MCC) pressure is a controlled parameter which strongly affects the overall engine performance, and the MCC Reference Pressure is the commanded value for this controlled parameter. The Low Pressure Fuel Pump (LPFP) discharge temperature and pressure and Low Pressure Oxidizer Pump (LPOP) discharge pressure represent engine inlet conditions. The need for retaining individual cluster center information is eliminated by the use of

regression equations. Furthermore, the regression equations provide the ability to interpolate between nominal cluster centers and thereby provide better coverage of the nominal space. Gaps in nominal coverage can occur since not all nominal states are typically available in a training set. There is one regression equation for each of the n parameters; the collection of regression equations is referred to as a *model set*.

Table 1: Parameters used as inputs and outputs for the Clustering Algorithm.

Parameter Description	Model Input	Model Output
MCC Pressure CH A1	x	
MCC Reference Pressure	x	
LPFP Discharge Pressure CH A	x	
LPFP Discharge Temperature CH A	x	
LPOP Discharge Pressure CH A	x	
MCC Coolant Discharge Pressure		x
MCC Coolant Discharge Temperature		x
LPOP Shaft Speed		x
LPFP Shaft Speed		x
OPOV Actuator Position		x
FPOV Actuator Position		x
HPFP Discharge Pressure		x
HPFP Coolant Liner Pressure CH A		x
FPB Chamber Pressure		x
PBP Discharge Pressure		x
HPOT Discharge Temperature		x
PBP Discharge Temperature CH B		x
Fuel Flowrate		x
HPFT Discharge Temperature CH A		x
HPOT Discharge Temperature CH A		x
HPFP Shaft Speed CH A		x

For fault detection, the model set provides an estimate of a nominal n -dimensional cluster based on the five inputs. As a result, each parameter has a residual, or difference between actual and predicted values, associated with it. The individual residuals are combined into a total residual, or *distance*, between the measured data point and the predicted n -dimensional nominal cluster. In this study, the five input parameters were used to estimate 16 output parameters. The outputs are listed in Table 1; these output parameters represent various temperatures, pressures, flowrates, valve positions and shaft speeds throughout the engine.

The use of the Clustering Algorithm for fault detection is summarized as follows:

1. A collection of regression equations, or model set, is selected.
- For each time slice:
 2. Each of the five input and sixteen output parameters is normalized by the operating range of the parameter under consideration.
 3. For each of the sixteen output parameters, a

normalized predicted value, S_p , is generated based on the a regression equation applied to the five inputs.

4. The difference, $d(i)$, between actual and predicted values is computed for each of the output parameters:

$$d(i) = S_a(i) - S_p(i)$$

where $S_a(i)$ is the normalized measured value for sensor i .

5. The individual difference values are combined into a total distance, D , as follows:

$$D = \sqrt{\sum_{i=1}^n [d(i)]^2}$$

where n is the total number of parameters in the multidimensional space ($n=16$).

6. In the study that considered historical ground test firing data, the total distance was compared to a preset event detection threshold. An engine fault was declared when the threshold was exceeded on multiple consecutive time slices.

Additional sensitivity to possible system anomalies could be achieved by monitoring the total distance for changes instead of thresholding the magnitude of the total distance. Furthermore, the individual parameter residuals could be used to provide some fault isolation information. If all parameters associated with a particular component exhibit changes in their residuals, a fault in that component is likely. Such fault isolation is useful since different actions may be required depending on the fault location. Furthermore, fault isolation information can be provided even in the event of a previously unencountered failure mode.

CLUSTERING ALGORITHM APPLICATION: MODEL SET GENERATION

The original Clustering Algorithm developed using ground test firing data relied on a database of nominal model sets in order to account for between-test variations. These variations arise due to changes in thrust profiles and venting schedules, differences in test duration and test stand, changes in Line Replaceable Unit (LRU), or component, combinations, and changes in engine mixture ratio. Many of these factors are also relevant for flight data. However, it is desirable to limit the number of model sets required for coverage of all engines of a given design. For this reason, preliminary studies were conducted to assess the impact of different engines, different missions and different thrust profiles on model prediction accuracy for flight data.

Four new Clustering Algorithm model sets were generated using flight data. Since the particular LRU combination that is flown is not generally tested on a test stand, the selection of ground test firing data to be used in generating models for flight is not straightforward. Furthermore, thrust profiles and engine inlet conditions vary widely from test to test; flight profiles are much more repeatable. Therefore, flight data sets were used to develop model sets in this study. Four different nominal model sets based on flight data were generated. Three model sets used data from a single engine on a single mission while the fourth

model set used data from three engines, each from a different mission.

When a single engine firing is used for model development, the data set is first reduced to a small number of cluster centers, typically 2.5% of the original number of data points, using a data clustering technique. Multivariate nonlinear functions are then constructed using least squares regression to predict these cluster centers as a function of the five input parameters. When multiple engine firings are used to create a model set, data from each firing is clustered separately. The cluster centers are then combined and regression coefficients are determined.

Data from five STS missions were considered for model development and evaluation: STS-044, STS-056, STS-058, STS-060 and STS-061. The three engines used in each STS mission are referred to as the Center (C), Left (L) and Right (R) engines. In addition, each engine on a mission has a numerical designation. Identical engine numbers do not indicate identical LRU combinations. Three of these missions were used for model generation: STS-058, STS-060, STS-061. As can be seen from Table 2, these three missions do not have any engines in common. In addition, each of the missions used for model generation has a slightly different power level profile; Figure 1 shows a typical flight power level profile. The actual power level achieved during the thrust bucket, the interval from about 30 to 70 seconds, is determined during flight. The portion of the profile immediately following the start transient and prior to the thrust bucket is also mission dependent. The data sets used to generate the single and multiple engine model sets are summarized in Table 3.

Table 2: Missions and engines used for Clustering Algorithm development and evaluation.

Mission	Center Engine	Left Engine	Right Engine
STS-044	2015	2030	2029
STS-056	2024	2033	2018
STS-058	2024	2109	2018
STS-060	2012	2034	2032
STS-061	2019	2033	2017

Each model set was tested on all data sets not used in the construction of that model. This includes data from all three engines of STS-044 and STS-056. STS-056 was selected because it contains Engine 2024 for which a model was created on STS-058. It should be noted, however, that both high pressure turbopumps on Engine 2024 were replaced between these two flights. Finally, STS-044 was selected because it is one of the two flights which experienced off-nominal engine behavior.

In evaluating the performance of the Clustering Algorithm, both the total distance and the individual parameter residuals were monitored. A small total distance, which is not

affected by nominal engine phenomena such as Solid Rocket Booster (SRB) separation and power-level changes, is desired. Flat individual parameter residuals, which indicate that the input parameters adequately predict the variations in the modeled parameter over time, are needed to achieve a flat total distance. Flat residuals are characterized by a relatively small standard deviation when computed over the entire mission following the start transient and prior to engine cutoff. Individual parameter residuals can also be examined for means which are offset from zero. Test-to-test parameter mean offsets have been attributed by data analysts, in large part, to hardware changeouts. Biasing schemes have been used to effectively deal with such offsets.[8] Therefore, in this study, variations in the residual were considered to be more important than the actual residual magnitude.

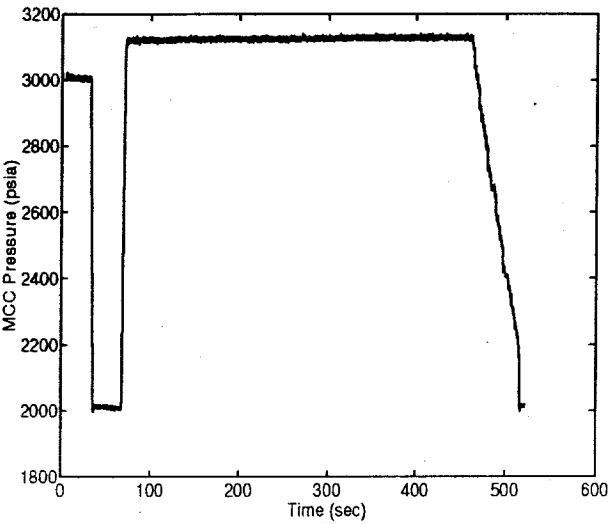


Figure 1. Typical Flight Profile of the SSME.

Table 3: Data used to generate Clustering Algorithm model sets.

Model Set Number	Model Set Created From
1	STS-058 C
2	STS-060 C
3	STS-061 C
4	STS-058 C STS-060 C STS-061 C

RESULTS AND DISCUSSION

Four model sets were created for the Clustering Algorithm. As indicated in Table 3, three of the model sets represent a single engine on a single mission, while the fourth model set was created using three engines, each from a different mission. Of primary interest is the ability of the Clustering

Algorithm to predict the nominal variations in the sixteen output parameters. The total distance, or combination of the individual parameter residuals, was also qualitatively addressed. For a nominal flight, flat individual parameter residuals are desired since they lead to a flat total distance.

For example, Model Set 4, based on data from multiple missions, was used to generate predictions for the left engine of STS-060. Plots depicting the total distance and selected individual model residuals are given in Figures 2 (a) - (d). The parameter residuals have been denormalized prior to presentation while the overall distance represents the combination of normalized residuals. Currently, each parameter residual is normalized by the nominal range of that parameter. The total distance shown in Figure 2(a) shows slight indications of power-level transitions and SRB separation. This is due to the fact that several individual parameter residuals were affected by these phenomena. As indicated by the typical flight power level profile shown in Figure 1, the engines throttle down for about 40 seconds, beginning at approximately 30 seconds following engine start, as the shuttle passes through the region of maximum dynamic pressure. At approximately 460 seconds a gradual deceleration is initiated to adhere to the 3-g throttle limit established for the astronauts. SRB separation occurs at approximately 120 seconds. The Low Pressure Fuel Pump (LPFP) shaft speed residual shown in Figure 2(b), for example, shows an increase coincident with SRB separation. An example of power-level dependency can be seen in the Fuel Preburner (FPB) chamber pressure residual shown in Figure 2(c). Consideration of an expanded input set and the selection of optimal regression equation forms could be investigated to address these dependencies.

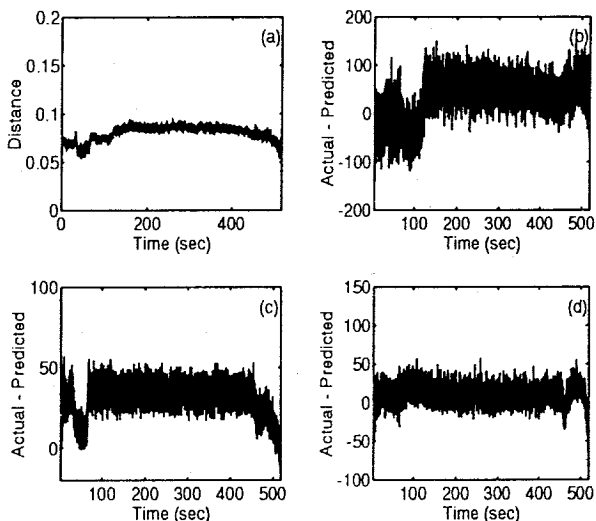


Figure 2. Selected Model 4 results on STS-060 Left Engine: (a). the combined distance value, (b). the LPFP shaft speed model residual, (c). the FPB chamber pressure model residual and (d). the HPFP discharge pressure model residual.

The performance of Model Set 4 on the left engine of STS-060 can be qualitatively contrasted to the performance of Model Set 1, based on data from a single mission, on the same data set. The overall distance is shown in Figure 3(a). The total distance

for Model Set 1 exhibits stronger power-level dependence than the total distance for Model Set 4. Likewise, the individual parameter residuals for Model Set 1, shown in Figures 3(b)-(d), show a stronger power-level dependence than the corresponding residuals generated by Model Set 4. The High Pressure Fuel Pump (HPFP) discharge pressure residuals shown in Figures 2(d) and 3(d), for example, both show slight shifts around the time of SRB separation. Changes in the residual with power level, however, are more pronounced for the predictions generated by Model Set 1. Although model sets based on single data sets, Model Sets 1, 2, and 3, were also observed to produce relatively flat distance plots on some data sets, the multiple engine model was more consistent in producing this behavior for the nominal data sets evaluated. These results indicate that using multiple data sets in training may provide better coverage of all possible conditions that will be encountered during flight and therefore will result in models that can more accurately predict performance parameters on a new mission.

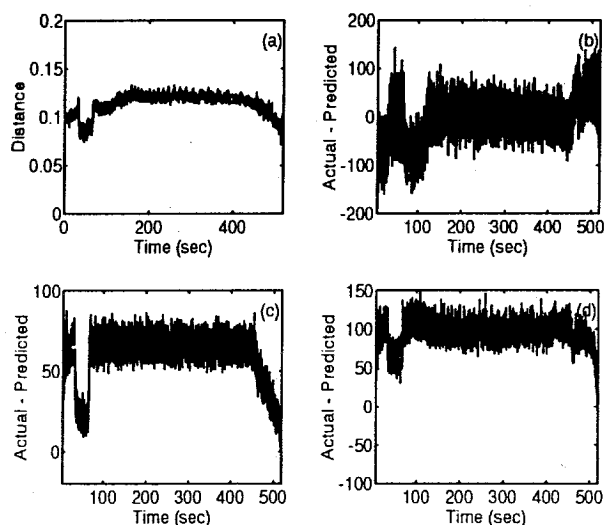


Figure 3. Selected Model 1 results on STS-060 Left Engine: (a). the combined distance value, (b). the LPFP shaft speed model residual, (c). the FPB chamber pressure model residual and (d). the HPFP discharge pressure model residual.

Engine hardware does not appear to play a large role in the ability of the regression equations to accurately predict behavior. Model Set 1, trained on data from the center engine of STS-058, Engine 2024, was applied to the data from the center engine of STS-056, also Engine 2024. The residual statistics for the left and right engines of STS-056 were comparable to and sometimes better than those for the center engine. This could be partially attributed to the fact that several LRU component changeouts occurred for engine 2024 between STS-056 and STS-058. Because these component changeouts are so frequent, hardware specific models are not practical and do not seem to be indicated. Rather, models that adequately capture all of the nominal phenomena expected during flight are required.

In addition to the nominal data sets described above, data from STS-044, a mission on which one engine experienced

apparent off-nominal behavior, were also considered. The left engine on STS-044 exhibited simultaneous upward shifts in the two A channels and downward shifts in the two B channels of the MCC pressure at 270 seconds into the mission. Although the shift represented a slight instrumentation problem, engineers in the control room should be alerted to the condition as soon as possible since an erroneous chamber pressure reading affects thrust and specific impulse and therefore the ability to successfully complete launch. One of the A channels of the MCC pressure is typically used as an input to the regression equations. For this mission, additional results were obtained by using a B channel as an input to the regression equations. In analyzing the residuals of some of the modeled parameters where an A channel was used as an input, Figures 4 (a) and (b), it can be seen that the parameter shift in the A channel physically corresponds to the change being experienced by the engine. When either B channel is used as an input, several parameters show predicted shifts opposite to those observed; the corresponding increase in residuals is illustrated in Figures 4(c) and (d). The overall distance plots are shown in Figures 5 (a) and (b). When an A channel is used as a Clustering Algorithm input, the total distance is not affected at 270 seconds. When a B channel is used as an input, the total distance shows a slight shift at 270 seconds. All of these results suggest an instrumentation problem in the two B channels of the MCC pressure. A model for the MCC chamber pressure could be used to arbitrate the discrepancy between the two channels. The average of the four MCC pressure channels is actually constant during this event because the controller is maintaining this average value at the commanded reference value. As the B channels approach the true (lower) value of the chamber pressure, the engine throttles up slightly to maintain the average MCC pressure value. In reality, the engine was operating at slightly less than the commanded chamber pressure prior to 270 seconds.

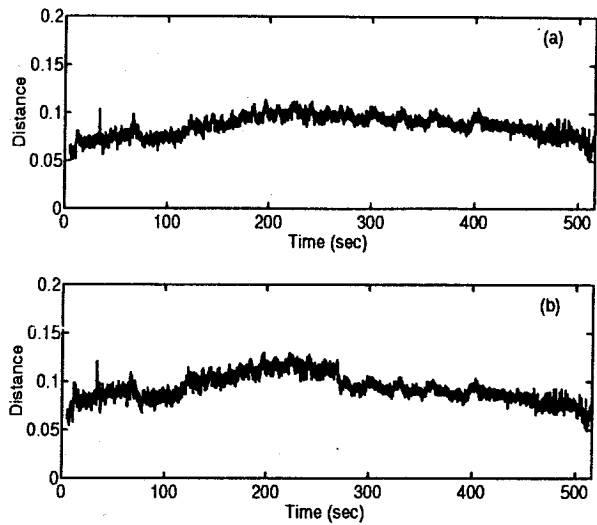


Figure 5. STS-044 results for the total distance with (a.) an MCC pressure A channel input and (b.) an MCC pressure B channel input.

CONCLUDING REMARKS

The Clustering Algorithm, an anomaly detection algorithm developed to enhance the current SSME redline system and originally trained and validated on ground test firing data, was trained on and applied to historical flight data. Since the Clustering Algorithm indicated off-nominal engine conditions significantly earlier than redline cutoff when applied to historical ground test firing failure data, the Clustering Algorithm is also being investigated for its ability to provide early diagnostic information to the JSC engineers responsible for monitoring the SSMEs during flight.

Flight data were used to generate four Clustering Algorithm model sets. These model sets were then applied to engines from five missions. Frequent LRU changeouts make model sets based on specific hardware impractical. Analysis of model residuals shows that model performance is independent of hardware configurations encountered in the training data, but rather is driven by the variety of examples available in the training data. Therefore, model sets based on multiple flights are indicated; such models are more likely to successfully capture a wide range of nominal engine phenomena.

The Clustering Algorithm regression equations were able to capture most of the variations in the parameters modeled; however, examination of individual parameter residuals revealed non-zero residual mean and some dependency on power-level transition and SRB separation. For model sets based on data from single and multiple engines, the nonzero residual means are primarily attributed to the test-to-test or flight-to-flight variation in hardware configurations, which could be addressed using biasing techniques. The residual dependency on scheduled events leads to a total distance that also varies with scheduled events. To address these dependencies, consideration of an expanded input set and the selection of optimal regression equation forms for each parameter could be explored.

This stage of the analysis indicates that the SSME

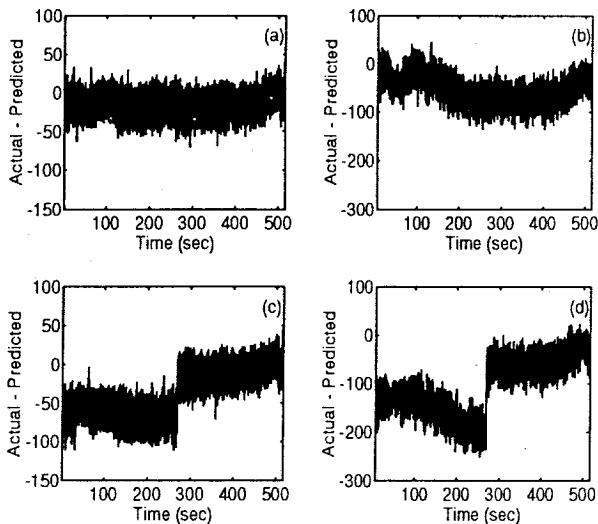


Figure 4. STS-044 results for parameters using an MCC pressure A channel as an input: (a). the LPOP shaft seed and (b). the preburner boost pump discharge pressure. STS-044 results for parameters using an MCC pressure B channel as an input: (c). the LPOP shaft speed and (d). the preburner boost pump discharge pressure.

parameters selected can be modeled across various nominal operating profiles and various engine configurations. Incorporation of the proposed modifications, with subsequent verification and validation by JSC and LeRC personnel, should allow the implementation of the Clustering Algorithm as an anomaly detection tool during flight.

REFERENCES

1. Roth, P., *Computer Program Contract End Item, Flight 4C Configuration, Space Shuttle Main Engine Controller Operational Program, Part 1*. CP406R0001, Revision F, Rockwell International/Rocketdyne Division, November 1988.
2. Cikanek, H.A., *Characteristics of Space Shuttle Main Engine Failures*, AIAA Paper 87-1939, June 1987.
3. Taniguchi, M.H., *Failure Control Techniques for the SSME, Phase I Final Report*, NASA CR-179224, 1986.
4. Nemeth, E., *Health Management System for Rocket Engines, Final Report*, NASA CR-185223, January 1990.
5. Hawman, M.H.; Galinaitis, W.S.; Tulpule, S.; and Mattedi, A., *Framework for a Space Shuttle Main Engine Health Monitoring System, Final Report*, NASA-CR-185224, May 1990.
6. Norman, A., *Rocketdyne Safety Algorithm, Space Shuttle Main Engine Fault Detection*, NASA CR-195356, July 1994.
7. Hawman, M.H.; Ruiz, C.A.; and Galinaitis, W.S., *Space Shuttle Main Engine Health Monitoring System - Fault Detection Algorithm Validation and Implementation, Final Report*, NASA-CR-970075, May 1994.
8. Bickmore, Timothy, *Real-Time Sensor Data Validation*, Proceedings of Conference on Advanced Earth-to-Orbit Propulsion Technology, May 17-19, 1994.